Resume of the proposed research topic on:

"Analysis of cognitive load using EEG signal"

by

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ABSTRACT

Electroencephalography(EEG) is the recording of electrical activity along the scalp. The flow of current due to firing of neurons in the brain results in a voltage fluctuation that is measured as EEG. EEG is used to measure cognitive activities, memory load and task engagement. It is difficult to assess cognitive load using analytical, subjective and behavioral method. The process is time consuming also interfere with main task. Physiological method like EEG reflects true condition of subject and direct assessment is also possible. EEG signal can be used in various clinical intervention such as epilepsy, sleep analyses, detection and monitoring brain injury and detection unusual brain states.

1. Introduction:

Electroencephalography(EEG) measures voltage fluctuations resulting from ionic current within the neurons of the brain. The measurement of the brain's response to a stimulus is called event-related potential (ERP). Human brain activity can be investigated non-invasively with the help of EEG with precision of milliseconds. EEG signal

amplitude is quite less, measured in microvolt(μV) and its spectrum of interest is upto 40 (Hz).

EEG used to be a first-line method of diagnosis for stroke, tumours and other focal brain disorders, but this use has decreased with the advent of high-resolution anatomical imaging techniques such as MRI and CT. EEG has limited spatial resolution, hut high millisecond-range temporal resolution (not possible with CT or MRI), therefore can be used to detect diseases and for diagnosis purpose.

Most of EEG signal power lies from 0 to 40 Hz and has amplitude in microvolts, within this frequency range (bands) sub-bands are analyzed . Depending on the application, different common bands of EEG are as follows

Delta:- This band contains frequency from 0.5 to 4 Hz. It is highest in magnitude and lowest in frequency. It is associated with deep stage 3 of Non-rapid eye movement sleep and quantify the depth of sleep.

Theta:- This band contains frequency from 3.5-7.5 Hz . It is normal in children up to 13 years and in sleep, but abnormal in awake adults. Theta wave arises from emotional stress, especially frustration or disappointment [1].

Alpha: - This band contain frequency from 7- 12.5 Hz and is usually best seen in the posterior regions of the head on each side, with the higher amplitude on the dominant side. It dominates when closing the eyes and in relaxation and vanishes when opening the eyes or while focusing on any system. It is mainly observed when adults are relaxed.

Beta: - This band has a frequency between 12.5 and 30 Hz and is usually seen on both sides in a symmetrical distribution; it is most evident frontally. This band is predominant in individuals who are caution, anxious or have their eyes open.

Gamma:- This band contain frequency from 30 Hz and greater. It is thought that it reflects the component of awareness. Beta and Gamma waves are associated to attention, perception and cognition [1]

EEG system cover all parts of brain by placing electrode on all part of head. There are two system of electrode placement on the scalp in special positions using [3]:
a) 10-20 international system: 21 electrodes b) 10-10 international system: 64 electrodes.

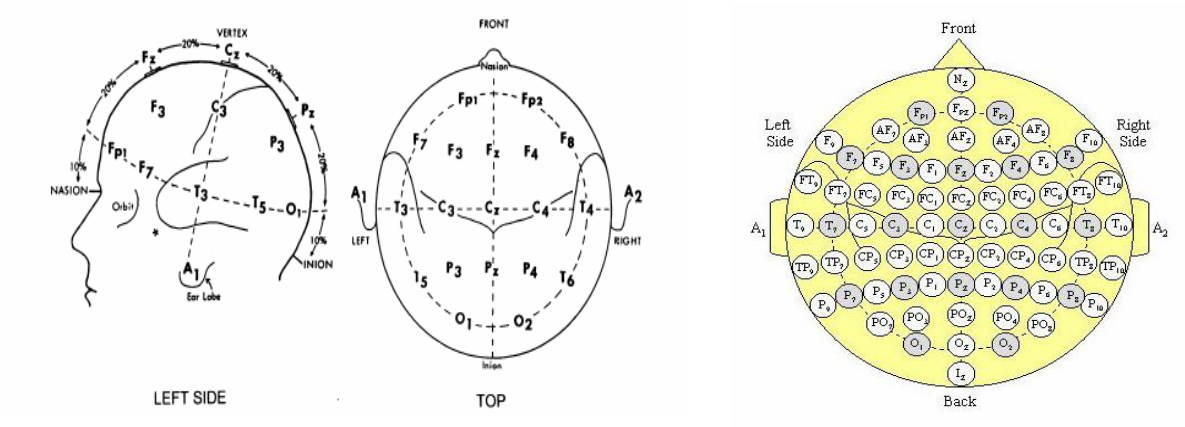

Fig1. a) 10-20 international system b) 10-10 international system

There are two different types of EEG signals depending on where the signal is taken in the head: scalp or intracranial. For scalp EEG, electrodes, are placed on the scalp with good mechanical and electrical contact. In intracranial EEG (IEEG), the EEG signal is obtained by special electrodes implanted in the brain surface during a surgery.

The brain (cerebrum) is formed of two cerebral hemispheres, right and left. Each cerebral hemisphere is formed of four lobes: 1) Frontal lobe: contains motor area 2) Parietal lobe: contains sensory area 3) Temporal lobe: contains area of hearing & memory 4) Occipital lobe: contains area of vision [4].

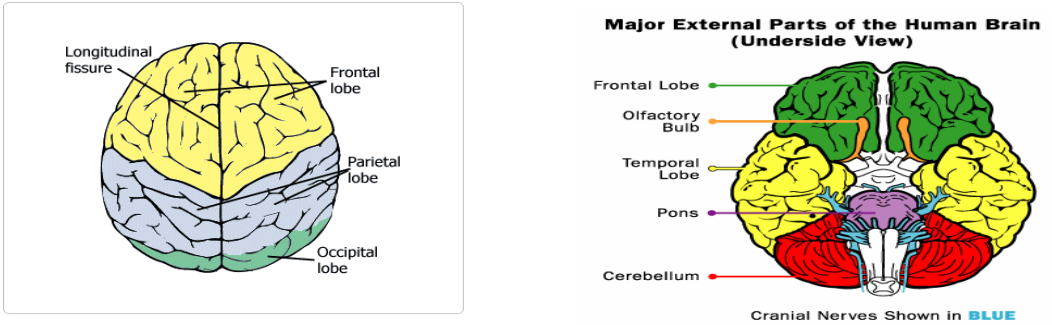

Fig 2. Brain Lobes

The pattern of connections between the electrodes and the recording channels is known as a montage. There are two basic types of EEG montage:

a) Referential: The potential difference is measured between an active electrode and an inactive reference electrode.

b) Bipolar: The potential difference is measured between two active electrodes.

Assessment of human cognitive states such as vigilance, task engagement and mental workload in an operational environment could be useful for developing more interesting and joyful way of learning. Subjective reports, biological measures (electroencephalography (EEG), electrocardiogram (ECG), surface electromyogram, electrooculography) , physical measures and hybrid methods are available to evaluate different cognitive states. However classifying cognitive states is challenging and expensive. Many methods have been employed to detect cognitive state changes; however EEG is the only physiological signal that has been shown to accurately reflect shifts in alertness, attention and workload that can be identified and quantified on a second-by-second time frame.

Human Brain uses two types of memory : short-term and long-term memory. Short term memory is also called working memory and long term memory is related to storage. Short term memory has limited capacity and long term memory has almost unlimited capacity. Working memory deals with brain system that provides temporary storage and manipulation of the information necessary for cognitive tasks such as language comprehension, learning and reasoning. Cognitive load is the load on working memory required to perform a task. Brain has limited cognitive processing capacity, any underloading or overloading of cognitive processing results in undesirable consequences such as degraded performance or failure to learn complex cognitive tasks or perform them correctly. Accordingly, scientists have expanded spotlight on keeping up the best level of cognitive load during cognitive process .Cognitive load measurement is also important for cognitive load theory(CLT). CLT is concerned with the design of instructional methods that efficiently use working memory to apply knowledge and skills to new situations .

Engagement is identified with forms including data gathering, visual checking, and maintained attention. Workload increases with working memory stack ,expanding trouble level mental task and other critical thinking task. The two parameters were shown to operate concordantly or independently, depending on the task environment, the level of

task demands, and the amount of effort required by the individual to complete the task [6].

2. Related Literature Review:

In 1995 , Pope and associates at NASA were the first to build up a framework that utilized diverse EEG-based data to indicate engagement level. A bio cybernetic loop was formed by modifying the mode of operation of a task set based on electroencephalographic (EEG) signals reflecting an operator's involvement in the task set. Cognitive functions like task Engagement, mental workload, learning and memory tasks have been correlated with EEG signal by BERKA *et al*[2] . The workload and engagement classifiers had been integrated into real-time, closed-loop automated computing systems to implement dynamic regulation and optimization of performance during a driving simulation task. Auditory attention detection through EEG signal has proposed by Biesmans[6]. AAD has the potential to take auditory prosthesis technology a step forward, by allowing enhancement of the actual attended speaker, while adapting to the acoustic scenario and shifting auditory attention.

Mahmoud[11] classified four different levels of cognitive workload using feature extraction based on statistical features followed by variable selection using stepwise regression and multiclass linear classification . Ren [12] investigated functional segregation and integration of brain networks over time by dynamic graph metrics derived from EEG signals during complex task. Kim [13] used EEG data in analyzing cognitive characteristics of driving workload caused by driver behavior.

3. Objectives of Research:

The main objective of the work will be to contribute novel technique for cognitive microstate assessment. Study systematic comparison of EEG features as well as the number/position of electrode for feature selection. Since we can categorize workload, this work will be useful to maintain optimum level of cognitive load for improving learning process. Hence it is decided to pursue following objectives:

1. To Find the representation of engagement and workload in EEG signals

2. To Classify different level of workload and relate it with engagement of the subject based on EEG signals
3. To discriminate the different types of load like intrinsic load , extraneous or ineffective load, and germane or effective load using EEG signal.
4. To develop a novel feature representing the workload content in EEG signals.
5. To develop engagement and workload data which will be publically available.

4. Methodology for Research:

In the view of above literature review in the field of cognitive engagement , it is decided to use following methodology for Research work:

- Cognitive load assessment using analytical, subjective and behavioral method is time consuming, not reliable and also interfere with main task. Physiological method like EEG reflects true condition of subject and direct assessment is also possible.
- To analyse cognitive microstates using EEG many intermediate steps have to be performed: artifact filtering, feature extraction, and classification.
- High pass filter is required with 0.5 Hz cutoff frequency to remove baseline drift, and a 50 Hz notch filter to delete the electrical interference. Physiological noises such as ocular and muscular artifacts can be removed by decomposing EEG signal using wavelet basis function such as coiflets.
- The resulting data will be analyzed and relevant features will be computed in time domain, frequency domain and time-frequency domain for each channel.

  The currently used features are:

$$power(P_e) = \frac{1}{samples}\sum_{-\infty}^{\infty}\left|eeg(t)\right|^2,$$

$$mean(\mu_e) = \frac{1}{samples}\sum_{1}^{samples} eeg(t),$$

$$std.deviation(\sigma_e) = \sqrt{\frac{1}{samples}\sum_{1}^{samples}\left(eeg(t)-\mu_e\right)^2},$$

  where *eeg (t)* represent single channel in time domain.

The Band power features are the most popular frequency domain feature in EEG used FFT, Power Spectra Density using Welch's method and STFT using a Hamming window algorithm.

The EEG signal is non-stationary, time-frequency domain can give dynamical changes information using Discrete Wavelet Transform (DWT) decomposition. Currently feature extraction for emotion recognition from EEG via DWT using db4 extracting energy, entropy, Root mean square (RMS), recursive energy efficiency (REE) etc of different band frequencies.

By studying the feature and conceiving the limitations of their representations, a novel feature representing the workload and its relation to engagement in EEG signals will be evolved.

5. Importance of study/society applications:-

5.1 International Status

Laine *et al* [7] classified low, medium and high mental workload using linear and non-linear artificial neural network. Cognitive load assessment in multimedia learning can be found in literature. Zarjam *et al*[9] proved that EEG as a highly promising method for measuring cognitive load in an arithmetic task. Tracking attention of driver during distracted driving using EEG is studied by wang *et al* [10] .Many Researchers are working in classifying workload based on EEG signal. Nilanjan Sarkar and his team from Vanderbilt university, USA working on EEG based workload classification in a virtual driving environment for autism spectrum disorders(ASD).

5.2 National Status

Consciousness levels was detected by Kartik. S *et al* [15] using discrete wavelet transforms on single channel EEG under simulated workload conditions. They belong to defence Bioengineering and Electro medical laboratory, Bangalore. The different waveforms like alpha, beta, theta and delta were studied and selected features were related with the consciousness levels. The consciousness levels detection is useful for estimating the subject's performance in certain selected

tasks which requires high alertness. The estimation was performed by analyzing signal properties of the EEG using features extracted through discrete wavelet transform with a moving window of 10 seconds with 90 percent overlap.

6. Proposed work plan/formulation and structure of study

Sr. No.	Activity	2	4	6	8	10	12	14	16	18	20	22	24
1	**Literature Survey**												
2	**Strength and weaknesses Identification of existing techniques.**												
3	**Problem Definition and feasibility study**												
4	**Design**												
5	**Implementation**												
6	**Testing**												
7	**Thesis Writing**												
8	**Publications**												

References:

1. N. Kamel, *EEG/ERP Analysis: Methods and applications*. CRC press, 2015.
2. 10/20 System Positioning Manual, Trans Cranial Technologies ldt. 2012.
3. William O. Tatum, "Handbook of EEG Interpretation," demos Medical, 2nd Ed.

4. A. T. Pope, E. H. Bogart, and D. S. Bartolome, “Biocybernetic system evaluates indices of operator engagement in automated task,” Biol. Psychol., vol. 40, no. 1–2, pp. 187–195, May 1995
5. Berka chris, Daniel J. Levendowski, Michelle N. Lumicao, “EEG Correlates of Task Engagement and Mental Workload in Vigilance, Learning, and Memory Tasks,” Aviation, Space, and Environmental Medicine., Vol. 78, No. 5, May 2007
6. W. Biesmans, N. Das, T. Francart and A. Bertrand, "Auditory-Inspired Speech Envelope Extraction Methods for Improved EEG-Based Auditory Attention Detection in a Cocktail Party Scenario," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 5, pp. 402-412, May 2017.
7. T. I. Laine, K. W. Bauer, J. W. Lanning, C. A. Russell and G. F. Wilson, "Selection of input features across subjects for classifying crewmember workload using artificial neural networks," in *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, vol. 32, no. 6, pp. 691-704, Nov 2002.
8. M. Mazher, A. Abd Aziz, A. S. Malik and H. Ullah Amin, "An EEG-Based Cognitive Load Assessment in Multimedia Learning Using Feature Extraction and Partial Directed Coherence," in *IEEE Access*, vol. 5, pp. 14819-14829, 2017
9. P. Zarjam, J. Epps and N. H. Lovell, "Beyond Subjective Self-Rating: EEG Signal Classification of Cognitive Workload," in *IEEE Transactions on Autonomous Mental Development*, vol. 7, no. 4, pp. 301-310, Dec. 2015.
10. Y. K. Wang, T. P. Jung and C. T. Lin, "EEG-Based Attention Tracking During Distracted Driving," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 23, no. 6, pp. 1085-1094, Nov. 2015.
11. R. Mahmoud, T. Shanableh, I. P. Bodala, N. V. Thakor and H. Al-Nashash, "Novel Classification System for Classifying Cognitive Workload Levels Under Vague Visual Stimulation," in *IEEE Sensors Journal*, vol. 17, no. 21, pp. 7019-7028, Nov.1, 1 2017.
12. S. Ren, J. Li, F. Taya, J. deSouza, N. V. Thakor and A. Bezerianos, "Dynamic Functional Segregation and Integration in Human Brain Network During Complex Tasks," in *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 25, no. 6, pp. 547-556, June 2017.

13. H. S. Kim, Y. Hwang, D. Yoon, W. Choi and C. H. Park, "Driver Workload Characteristics Analysis Using EEG Data From an Urban Road," in *IEEE Transactions on Intelligent Transportation Systems*, vol. 15, no. 4, pp. 1844-1849, Aug. 2014.
14. Paas, F., Tuovinen, J. E., Tabbers, H., & Van Gerven, P. W. (2003b). Cognitive load measurement as a means to advance cognitive load theory. *Educational Psychologist, 38*, 63–71.
15. Karthik S. N, Mohanavelu K, "Consciousness Levels Detection Using Discrete Wavelet Transforms on Single Channel EEG Under Simulated Workload Conditions," in Defence Life Science Journal, Vol. 2, No. 4, pp. 391-398, October 2017.

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